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Does energy consumption contribute to climate change? Evidence from major regions of the world

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ABSTRACT

This study is a contribution to the on-going debate over whether there is a relationship between energy consumption and climatic change variables, although the developed regions are among the most energy intensive economies in the world, little attention has been paid to the features of their energy consumption and climatic variations. Therefore, this study empirically investigates the two variables dynamic relationship in five broader regions of the world i.e., South Asia, Middle East and North Africa (MENA region), Sub-Saharan Africa, East Asia and Pacific and the aggregate data of the World. The major climatic variables include atmospheric, topographic, living organisms threatened; water system and growth factors are used to investigate energy–climate nexus over a period of 1975–2011. The results of the study indicate that there exists a long-run equilibrium relationship between energy consumption and climatic variables which shows climatic variations due to changes in energy consumption in different regions of the world. Although, the causality results are mixed among regions, we do find a systematic pattern. The present study find evident of unidirectional causality between the electric power consumption and climatic factors in the World's selected region. Sound and effective energy consumption strategy may reduce the burden of global warming situation in the world.

Contents

1. Introduction

Changes in temperature, precipitation, sea level, and the frequency and severity of extreme events likely affect on how much energy is produced, delivered, and consumed in the different regions of the World. Many factors, both natural and human, can cause changes in Earth's energy balance, i.e., changes in the greenhouse effect, which affects the amount of heat retained by Earth's atmosphere, variations in the sun's energy reaching Earth and changes in the reflectivity of Earth's atmosphere and surface [1]. The World Meteorological Organization (WMO) suggests 30 years as a standard time span for defining climate of a region. Common examples of climate are tropical, polar, marine and Mediterranean [2]. The future climate is already set over this time period and the consequences

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cannot be ignored [3]. Climate varies from place to place, depending on latitude, distance to the sea, vegetation, orography and other factors. Similar to weather, the climate variability also occurs at different time scales. The long term mean of the climate at a place is very important for our understanding since this determines many factors which are useful for human living [4].

The worldwide energy consumption in 2006 was close to 498 exajoules. This is equivalent to an energy convergence of 15.8TW into the populated regions, where energy is consumed and dissipated into the atmosphere as heat. Although energy consumption is sparsely distributed over the vast Earth surface and is only about 0.3% of the total energy transport to the extratropics by atmospheric and oceanic circulations, this anthropogenic heating could disrupt the normal atmospheric circulation pattern and produce a far-reaching effect on surface air temperature [5]. Table 1 shows the data trend of the variables for the ready reference.

The increasing threat of global warming and climate change has focused attention on the relationship between energy consumption and environmental pollutants [6]. Dolsak [7] analyzes factors affecting countries' commitment to mitigating global climate change within the scope of existing international institutions. A theoretical model of governments' decision making is presented and tested for 91 countries. The empirical analysis suggests that national commitment is significantly affected by the national government's incentives and the ability to affect the global level of GHG emissions, impacted more by the incentives than by the ability, and not affected by the aggregate levels of economic benefits. Leckebusch and Ulbrich [8] examine the relationship between cyclones and extreme wind events over Europe using global as well as regional climate model simulations. Climate change simulations based on the Special Report on Emission Scenarios (SRES) A2 and B2 are used. The results reveal that changes occur in particular with respect to the A2 scenario for extreme cyclone systems, while for B2 the changes are less pronounced. Especially over western parts of Central Europe, the track density of extreme cyclones increases for A2, accompanied by a tendency towards more intense systems. Swim and Becker [58] examines German versus U.S. residents' (predominantly students') efforts to engage in direct and indirect behaviors that lessen their personal contribution to greenhouse gases. The results show that Germans are more energy reduction behaviors because they were more likely to endorse biospheric environmental concerns, less likely to endorse egoistic environmental concerns, less likely to think that personal costs of energy reduction behaviors were important, and more likely to think ethical considerations were important. Sultan [9] examines the export-GDP nexus and electricity-GDP nexus in Mauritius for the period of 1970–2009. The multivariate Granger-causality analysis indicates that electricity and exports Granger-cause economic growth in the long-run. Fan et al. [10] focuses on the vulnerability of electricity demand due to the impact of climate change. The results show that electricity demand of all sectors is more sensitive to the heat pressure than cold pressure. Different electricity demand vulnerability to climate warming exist in different sectors, ranked from higher to lower by primary industry, tertiary industry, secondary industry and residential sector.

Al-mulali et al. [11] explored the relationship between urbanization, energy consumption, and CO_2 emission in the MENA countries during the period 1980–2009. The results show that there was a long-run bidirectional positive relationship between urbanization, energy consumption, and CO_2 emission. However, the significance of the long-run relationship between urbanization, energy consumption, and CO_2 emission varied across the countries based on their level of income and development. Borgstede et al. [12] explores public opinions regarding climate change and mitigation options and examines how psychological factors determine self-reported energy-efficient behavior. The results of an opinion poll conducted in 2005 and 2010 are compared. The number of respondents favoring new technologies as a way to reduce emissions was substantially lower in 2010 than in 2005, whereas there was an increase in the number of people who acknowledged that lifestyle changes are necessary to counteract climate changes. An analysis of the 2010 survey revealed that respondents with pro-environmental attitudes towards global warming favor significantly increased use of renewable energy technologies and greater engagement in energy-efficient behaviors. Ke et al. [13] examines the Energy-Saving Performance Contract (ESPC) of an office building by applying IPMVP Option D in combination with the energy analysis model established for the building by eQUEST simulation software to calibrate energy consumption simulation results using actual electricity billing data. The results indicate that, compared to actual energy consumption, the mean bias error (MBE) and root mean square error (RMSE) for uncalibrated simulation results are 24.48% and 125,050, whereas the MBE and RMSE for calibrated simulation is 0.37% and 34,197. When lighting power density increases or decreases by 50%, overall energy consumption decreases by 30.78% or increases by 31.19%, respectively. Therefore, illumination density has the greatest impact on energy consumption. Streimikiene and Siksnelyte [14] examine the impact of the electricity market regulation on generating technologies, including renewable in Lithuanian and Poland. The results reveal that the main driving forces behind the rationale for reform, electricity reform characteristics, the impact of electricity market reform on electricity prices and electricity market reform and non-reform related factors that have influenced investor's choice for a specific generation technology or a technology mix.

Akhmat et al. [15] investigate the relationship between greenhouse gas (GHG) emissions, energy mix and carbon emissions in the panel of 35 developed countries. The results conclude that electricity production from oil, gas, and coal sources increases the GHG emissions and air pollution in the region, however, the intensity is far less that through fossil fuel. In another study of Akhmat et al. [16] examine the cause-effect relationship between environmental pollutants and energy consumption in the selected SAARC countries, over a period of 1975–2011. The results conclude that energy consumption acts as an important driver to increase environmental pollutants in SAARC countries. Khan et al. [17] examines the causal relationship between energy consumption and greenhouse gas emission for seven largest regions of the World. The results show that the energy consumption Granger causes greenhouse gas emission but not vice versa. Mudakkar et al. [18] investigate the long-run relationship between economic growth, energy consumption, environment and natural resources in Pakistan by using a data from 1975 to 2011. The results support the conjunction of some unidirectional causality, feedback hypothesis and neutrality hypothesis between the variables in a country.

The above discussion confirms the strong correlation between energy consumption and climate change variables. In the subsequent sections, an effort has been made to find the empirical investigation on energy consumption and five broad categories of climatic change variables i.e., atmosphere, topography, living organisms threatened, water system and economic growth in the context of different regions of the world.

The study divided into following sections: after introduction which is presented in Section 1 above, section shows data source and methodological framework. Results are discussed in Section 3. Section 4 concludes the study.

2. Data source and methodological framework

The present study is based on annual time series data covering the time period from 1975 to 2011 for South Asia, Middle East and North Africa (MENA), Sub-Saharan Africa, East Asia and Pacific and

Table 1
Data view of the variables.
Source: World Bank [19] and ECV [20].

Aggregate data of the regions	Indicator Name	1975	1980	1985	1990	1995	2000	2005	2011
MENA	Electric power consumption (kWh per capita)	385.9589	658.9411	948.1167	1167.62	1415.052	1746.85	2140.2	2704.733
	CO_2 emissions from transport (% of total fuel combustion)	22.31333	23.12628	26.44838	24.69141	22.99968	23.654	23.31593	22.79868
	Arable land (% of land area)	4.631538	4.391027	4.631876	4.777036	5.092618	4.760015	4.870516	4.813974
	Urban population growth (annual %)	4.418982	4.537251	4.401154	4.396551	3.754324	2.6188	2.764785	2.425913
	Agriculture, value added (% of GDP)	6.795582	7.215304	9.013639	10.17364	9.5155	8.151535	6.998349	7.2415
	Combustible renewables and waste (% of total energy)	1.912398	1.248463	1.000851	0.860941	0.736994	0.688765	0.61629	0.525761
	GDP per capita (current US$)	1171.182	2536.302	2344.489	2105.601	2437.975	3020.422	4298.73	8462.2
	Industry, value added (% of GDP)	61.61465	56.64745	42.5561	43.40379	42.10966	45.85242	50.65324	55.6235
	GDP per unit of energy use (PPP $ per kg of oil equivalent)	4.2012	4.175139	3.909541	4.100373	4.105525	4.462201	4.648834	5.338129
	Population growth (annual %)	2.818766	3.199124	3.207222	3.389832	2.606495	1.926258	2.020529	1.929511
South Asia	Electric power consumption (kWh per capita)	102.7706	125.3677	172.4472	242.837	320.395	352.2685	424.2892	605.1593
	CO_2 emissions from transport (% of total fuel combustion)	21.24537	20.7176	17.58341	15.38718	15.16276	11.71464	10.61348	11.43566
	Arable land (% of land area)	42.436	42.53245	42.63853	42.67473	42.35675	42.61973	41.88003	41.31778
	Urban population growth (annual %)	4.0256	4.328923	3.522284	3.270318	2.918332	2.662588	2.648757	2.570275
	Agriculture, value added (% of GDP)	37.07562	34.53766	30.8541	28.88884	26.28724	23.55163	19.2257	18.81664
	Combustible renewables and waste (% of total energy)	60.53887	58.04291	50.62459	43.90287	38.25455	34.50197	31.36781	26.70122
	GDP per capita (current US$)	171.3853	264.1109	294.9814	362.0093	385.2373	450.7147	696.8783	1416.131
	Industry, value added (% of GDP)	22.32644	24.1388	25.00145	25.93772	26.76565	25.661	27.92157	26.60109
	GDP per unit of energy use (PPP $ per kg of oil equivalent)	1.2412	1.561842	2.097182	2.586965	3.060645	3.665799	4.743589	6.061074
	Population growth (annual %)	2.345947	2.417817	2.309294	2.20608	2.022052	1.773379	1.536293	1.340424
Sub-Saharan Africa	Electric power consumption (kWh per capita)	394.2142	478.454	529.9852	536.8865	511.778	523.381	543.6952	534.9305
	CO_2 emissions from transport (% of total fuel combustion)	20.03103	19.64915	18.53044	18.0518	18.65647	20.22884	22.11138	23.7628
	Arable land (% of land area)	6.202102	6.324854	6.50138	6.706573	7.158539	7.338453	8.109428	8.616258
	Urban population growth (annual %)	4.841381	4.783142	4.489046	4.539593	4.244026	3.905932	3.822641	3.927188
	Agriculture, value added (% of GDP)	19.74935	18.19276	21.34408	20.73675	19.96077	17.43973	17.36612	15.62852
	Combustible renewables and waste (% of total energy)	61.11137	58.07321	55.88297	57.29198	58.12695	59.22328	57.65758	57.64813
	GDP per capita (current US$)	405.8909	709.7386	478.9335	596.8458	563.5924	516.1671	861.1318	1438.263
	Industry, value added (% of GDP)	33.05886	38.31449	34.01215	34.28444	32.44271	34.08099	32.65757	32.27388
	GDP per unit of energy use (PPP $ per kg of oil equivalent)	1.4256	1.5248	1.640745	1.989211	2.093796	2.36173	2.941988	3.802452
	Population growth (annual %)	2.747709	2.857382	2.887301	2.814934	2.72972	2.698499	2.6582	2.708662
East Asia and Pacific	Electric power consumption (kWh per capita)	571.6852	712.8834	836.9744	1075.381	1368.9	1647.687	2243.316	3263.545
	CO_2 emissions from transport (% of total fuel combustion)	11.95853	12.33969	12.14863	12.52186	12.90185	14.29988	12.2285	11.60185
	Arable land (% of land area)	8.62947	8.782382	10.02258	10.26451	9.677466	10.03266	10.00454	9.809014
	Urban population growth (annual %)	2.622882	2.919798	3.550693	3.427731	3.215836	2.947755	3.0883	2.601056
	Agriculture, value added (% of GDP)	14.95414	12.2781	11.1914	9.84212	7.506287	5.853674	4.735165	4.296744
	Combustible renewables and waste (% of total energy)	22.8652	20.10064	19.15577	16.69232	14.25618	12.81862	10.10244	8.240218
	GDP per capita (current US$)	642.0526	1155.151	1391.859	2581.006	4194.546	3953.912	4699.189	8500.775
	Industry, value added (% of GDP)	39.31555	40.89791	38.94585	38.18083	36.9917	35.08486	33.89531	32.86902
	GDP per unit of energy use (PPP $ per kg of oil equivalent)	1.20125	1.546683	2.294993	2.820867	3.404429	3.989368	4.411694	5.285875
	Population growth (annual %)	1.915889	1.474842	1.507991	1.498695	1.2042	0.95198	0.756562	0.689737
World	Electric power consumption (kWh per capita)	1354.412	1586.296	1718.845	2120.54	2195.71	2385.443	2663.017	3044.221
	CO_2 emissions from transport (% of total fuel combustion)	19.76923	19.74143	20.41351	19.51218	20.38437	21.27432	20.41652	19.42624
	Arable land (% of land area)	10.23455	10.35776	10.6959	10.81553	10.72625	10.63708	10.72657	10.7675
	Urban population growth (annual %)	2.535521	2.619081	2.643881	2.598245	2.354013	2.181981	2.236926	2.11607
	Agriculture, value added (% of GDP)	9.242602	7.569893	6.946434	6.173187	4.942842	3.983701	3.376014	3.120929
	Combustible renewables and waste (% of total energy)	12.36979	11.91057	12.48581	10.15911	10.32191	10.06772	9.589217	9.813498
	GDP per capita (current US$)	1447.128	2502.737	2611.004	4214.156	5303.617	5387.443	7139.987	10195.81
	Industry, value added (% of GDP)	36.61383	36.96208	34.78518	33.01016	30.96061	29.39436	28.427	26.71195
	GDP per unit of energy use (PPP $ per kg of oil equivalent)	1.4256	2.009343	2.768721	3.035617	3.67498	4.421164	5.190933	6.449624
	Population growth (annual %)	1.869887	1.747188	1.731411	1.719234	1.489475	1.324237	1.213446	1.179687

World aggregate data. The data divides in to six broad categories of the variables i.e., energy consumption which is measured by electric power consumption, atmospheric variables include average precipitation, carbon dioxide emissions, industrial nitrous oxide emissions, methane emissions from livestock and drought, floods and extreme temperature, topographic variables includes urbanization, forest depletion, mineral resource depletion and arable land, living organisms threatened includes bird species, mammal species, plant species and fish species threatened, water system variables includes agriculture irrigated land, ground water discharge and combustible waste, and finally, growth variables includes industry value added, GDP per capita, GDP per unit use of energy and population growth. The data set of the variables is taken from *World Development Indicator* which is published by World Bank [19] and Essential Climate Variables (ECV) [20], data access matrix which is published by Global Climate Observing Systems (GCOS).

2.1. Theoretical frame work

The role of energy in climate change variables are underlined in a number of studies (see for example, Dale [21], McMichael et al. [22], Harry and Morad [23] and Holmes and Reinhart [24]). Climate is the result of a delicate balance between several elements, which include:

- atmosphere,
- water systems,
- living organisms and
- topography.

These elements determine various factors that govern the climate. These factors are called climatic variables. Of these, the most important factors that are taken into account are rain, atmospheric pressure, wind, humidity, and temperature [25].

Scientists agree that humans very likely bring about changes in climate through various activities. This can happen at an individual level or at a group level. Each individual in today's world plays a role, directly or indirectly, in contributing his or her bit to climate change [26]. For example,

- Electric power is generated mainly by thermal power plants. These release a huge amount of greenhouse gases (GHGs) [27].
- Vehicles run on petrol or diesel, both are fossil fuels. These release a huge amount of GHGs [28].
- The more people consume luxury goods, essentials, and household goods, the more industry flourishes. Most industries are run on power generated from fossil fuels. To add to this, the more we consume the more waste we generate [29].
- A great deal of waste that we generate, such as plastics, does not get degraded and remains in the environment for many years, causing damage. The use of trees in large quantities for construction of houses leads to further depletion of forests [30].
- Changes in aerosol level causes scattering of sunlight and hence impacts global energy balance [31].

Climatologists examine weather patterns and other data from the past in order to make predictions about Earth's overall climate in the future. They make such predictions by creating climate models. Climate models are sets of mathematical equations. These mathematical equations describe the relationships among many atmospheric properties, or variables. Such properties include wind speed, air pressure, temperature, precipitation, and the concentrations of many gases in the air. Climate models allow scientists to predict how a change in each variable will affect the other variables and ultimately the global climate on Earth [32].

This study developed a comprehensive model based upon number of previous studies on the same topic which comprises six broad categories of energy consumption and climate change variables in the context of five broad regions of the world i.e., South Asia, MENA, Sub-Saharan Africa, East Asia and Pacific and aggregate data of World i.e.

$$\ln(\mathrm{EPC})_t = \alpha_0 + \alpha_1 \ln(\mathrm{ATM})_t + \alpha_2 \ln(\mathrm{TOPO})_t + \alpha_3 \ln(\mathrm{LOT})_t + \alpha_4 \ln(\mathrm{WS})_t + \alpha_5 \ln(\mathrm{GROWTH}) + \varepsilon_t \quad (1)$$

where α_0 represents intercept, α_1–α_5 are the slope of the respective variables, ln(EPC) is the natural logarithm of electric power consumption, ln(ATM) is the natural log of atmospheric variables i.e., average precipitation, carbon dioxide emissions, industrial nitrous oxide emissions, methane emissions from livestock and droughts, floods and extreme temperatures, ln(TOPO) is the natural log of topographic variables i.e., forest depletion, mineral resource depletion, arable land, and urbanization, ln(LOT) is the natural log of living organisms threatened i.e., bird species, mammal species, plant species, and fish species threatened, ln (WS) is the natural log of water system which contains ground water recharge, agriculture irrigated land and combustible waste, ln(GROWTH) is the natural log of growth variables which comprises GDP per capita, industry value added, GDP per unit use of energy and population growth and ε is the white noise error term. The dependent and independent variables used in this study are listed in Table 2. Electric power consumption (EPC) is used as a dependent variable for the study while, independent variables are atmosphere, topography, living organisms threatened, water system and economic growth variables.

A simple theoretical model has been extracted from previous studies to show energy consumption and climate change variables in five broad regions of the world are shown in Fig. 1.

2.2. Econometric framework

Comparable to all other techniques, that utilize time series data, it is essential to distinguish that unless the diagnostic tools used account for the dynamics of the link within a sequential 'causal' framework, the intricacy of the interrelationships involved may not be fully confined. For this rationale, there is a condition for utilizing the advances in time-series version. The following sequential procedures are adopted as part of methodology used.

In order to confirm the degree, these series split univariate integration properties; we execute unit-root stationarity tests. The Augmented Dickey–Fuller (ADF) and Phillips Perron (PP) test is a suitable testing procedure that is based on the null hypothesis that a unit root exists in the autoregressive representation of the time series.

The most common procedure in choosing the optimal lag length is to estimate a VAR model including all our variables in non-differenced data. This VAR model should be estimated for a large number of lags, then reducing down by re-estimating the model for one lag less until we reach zero lags. In each of these models, we inspect the values of Akike Information Criteria (AIC) and the Schwarz Information Criteria (SIC) criteria. The model that minimizes the AIC and the SBC is selected as the one with the optimal lag length.

In general, five distinct models can be considered. Although the first and the fifth model are not that realistic and they are also implausible in terms of economic theory, therefore, the problem reduces to a choice of one of the three remaining models (models 2–4).

Model 1: No intercept or trend in CE or VAR.

Model 2: Intercept (no trend) in CE, no intercept or trend in VAR.

Table 2
List of variables.

Variables	Measurement	Expected sign	Data source
Dependent variable: energy consumption			
Electric power consumption (EPC)	Kilo watt hour (kWh) per capita	World Bank [19]	
Atmosphere (ATM)			
Average Precipitation in depth (AP)	Millimeter (mm) per year	Positive	ECV [20]
CO_2 emissions from transport (CO_2)	% of total fuel combustion	Positive	World Bank [19]
Industrial Nitrous oxide emissions (INE)	thousand metric tons of CO_2 equivalent	Positive	World Bank [19]
Methane emissions from livestock (ME)	thousand metric tons of CO_2 equivalent	Positive	World Bank [19]
Droughts, floods and extreme temperature (DFET)	% of population, average 1980–2009	Positive	ECV [20]
Topography (TOPO)			
Forest depletion (FD)	Adjusted savings: net forest depletion (current US$)	Positive	World Bank [19]
Mineral resource depletion (MRD)	Adjusted savings: mineral depletion (Current US$)	Positive	World Bank [19]
Arable land (AL)	% of land area	Positive	World Bank [19]
Urbanization (URB)	Urban population growth (annual %)	Positive	World Bank [19]
Living organisms threatened (LOT)			
Bird species (BS)	In numbers	Positive	ECV [20]
Mammal species (MS)	In numbers	Positive	ECV [20]
Plant species (PS)	In numbers	Positive	ECV [20]
Fish species (FS)	In numbers	Positive	ECV [20]
Water system (WS)			
Ground water recharge (GWR)	% of total freshwater withdrawal	Positive	ECV [20]
Agriculture irrigated land (AIL)	% of total agricultural land	Positive	World Bank [19]
Combustible renewables and waste (CW)	% of total energy	Positive	World Bank [19]
Economic growth (GROWTH)			
GDP per capita (GDPPC)	Current US$	Positive	World Bank [19]
Industry value added (IVA)	% of GDP	Positive	World Bank [19]
GDP per unit use of energy (GDPENRG)	PPP $ per kg of oil equivalent	Positive	World Bank [19]
Population growth (PG)	Annual %	Positive	World Bank [19]

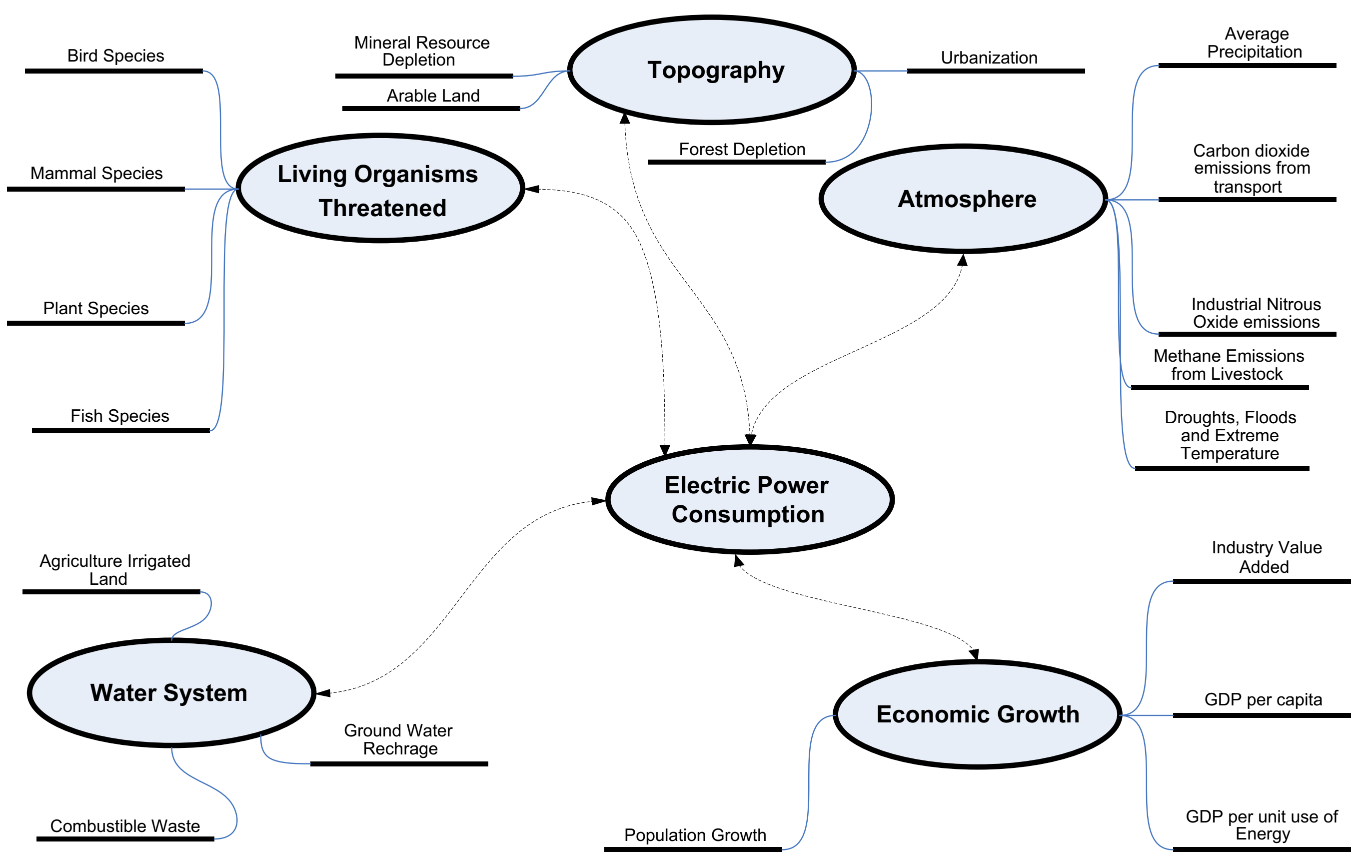

Fig. 1. Research framework for energy and climate change variables.
Source: Self extract.

Model 3: Intercept in CE and VAR, no trends in CE and VAR.
Model 4: Intercept in CE and VAR, linear trend in CE, no trend in VAR.
Model 5: Intercept and quadratic trend in the CE intercept and linear trend in VAR.

For the intention of investigating the long-run relationship among the variables, they must be co-integrated. In the multivariate case, if the I(1) variables are linked by more than one co-integrating vector, the Engle–Granger procedure is not applicable. The test for co-integration used here is the likelihood ratio put forward by Johansen and Juselius [33], indicating that the maximum likelihood method is more appropriate in a multivariate system. Therefore, this method is used in this study to identify the number of co-integrated vectors in the model. The Johansen and Juselius method has been developed in part by the literature available in the field and reduced rank regression. The co-integrating vector ‘*r*’ is defined by Johansen as the maximum Eigen-value and trace test. There is ‘*r*’ or more co-integrating vectors. Johansen and Juselius [33] and Johansen [34] propose that the multivariate co-integration methodology can be defined as

$$\ln(\text{EPC}) = \ln(\text{ATM}, \text{TOPO}, \text{LOT}, \text{WS}, \text{GROWTH}) \tag{2}$$

which is a vector of $P=5$ elements. Considering the following autoregressive representation:

$$Y_t = \pi_0 + \sum_{T=1}^{K} \pi_i Y_{t-1} + \mu_t$$

Johansen's method involves the estimation of the above equation by the maximum likelihood technique, and the testing of the hypothesis Ho, $(\pi = \Psi\xi)$ of ‘*r*’ co-integrating relationships, where ‘*r*’ is the rank or the matrix $\pi(0\angle r\angle P), \Psi$ is the matrix of weights with which the variable enters co-integrating relationships and ξ is the matrix of co-integrating vectors. The null hypothesis of non-cointegration among variables is rejected when the estimated likelihood test statistic $\phi_i\{=-n\sum_{t=r+1}^{p}\ln(1-\hat{\lambda}_i\}$ exceeds its critical value. Given estimates of the Eigen-value $(\hat{\lambda}_i)$ the Eigen-vector (ξ_i) and the weights (Ψ_i), we can find out whether or not the variables in the vector are co-integrated in one or more long-run relationships among the dependent variables.

If the time series are integrated at first difference, then one could run regressions in their first differences. However, by taking first differences, we drop the long-run correlation that is stored in the data. This means that one needs to use variables in levels as well. Error Correction Model (ECM) incorporates variables both in their levels and first differences. ECM depicts the short-run disequilibrium as well as the long-run equilibrium adjustments between variables. ECM term having negative sign and value between “0 and 1” specifies convergence of the model towards long-run equilibrium.

Following Pesaran et al. [35], we assemble the vector autoregression (VAR) of order *p*, denoted VAR (*p*), for the following growth function:

$$Z_t = \mu + \sum_{i=1}^{p} \beta_i z_{t-i} + \varepsilon_t \tag{3}$$

where z_t is the vector of both x_t and y_t, where y_t is the dependent variable defined as electric power consumption (EPC), x_t is the vector matrix which represents a set of explanatory variables and t is a time or trend variable. According to Pesaran et al. [35], y_t must be I(1) variable, but the regressor x_t can be either I(0) or I(1). We further developed a vector error correction model (VECM) as follows:

$$\Delta z_t = \mu + \alpha t + \lambda z_{t-1} + \sum_{i=1}^{p-i} \gamma_t \Delta y_{t-i} + \sum_{i=1}^{p-1} \gamma_t \Delta x_{t-i} + \varepsilon_t \tag{4}$$

where Δ is the first-difference operator. The long-run multiplier matrix λ as

$$\lambda = \begin{bmatrix} \lambda_{YY}\lambda_{YX} \\ \lambda_{XY}\lambda_{XX} \end{bmatrix}$$

The diagonal elements of the matrix are unrestricted, so the selected series can be either I(0) or I(1). If $\lambda_{YY}=0$, then Y is I(1). In contrast, if $\lambda_{YY}<0$, then Y is I(0).

The VECM procedures described above are imperative in the testing of at most one cointegrating vector between dependent variable y_t and a set of regressors x_t. To derive model, we followed the postulations made by Pesaran et al. [35] in Case III, that is, unrestricted intercepts and no trends. After imposing the restrictions $\lambda_{YY}=0$, $\mu \neq 0$ and $\alpha=0$, the hypothetical function can be stated as the following unrestricted error correction model (UECM):

$$\begin{aligned} \Delta \ln(EPC)_t = {} & \beta_0 + \beta_1 \ln(EPC)_{t-1} + \beta_2 \ln(ATM)_{t-1} \\ & + \beta_3 \ln(TOPO)_{t-1} + \beta_4 \ln(LOT)_{t-1} \\ & + \beta_5 \ln(WS)_{t-1} + \beta_6 \ln(GROWTH) \\ & + \sum_{i=1}^{p} \beta_7 \Delta \ln(EPC)_{t-i} + \sum_{i=0}^{q} \beta_8 \Delta \ln(ATM)_{t-i} \\ & + \sum_{i=0}^{r} \beta_9 \Delta \ln(TOPO)_{t-i} + \sum_{i=0}^{s} \beta_{10} \Delta \ln(LOT)_{t-i} \\ & + \sum_{i=0}^{t} \beta_{11} \Delta \ln(WS)_{t-i} + \sum_{i=0}^{u} \beta_{12} \Delta \ln(GROWTH)_{t-i} + u_t \end{aligned} \tag{5}$$

where Δ is the first-difference operator and u_t is a white-noise disturbance term. Eq. (5) also can be viewed as an ARDL of order (*p*, *q*, *r*, *s*, *t*, *u*). Eq. (5) indicates that energy consumption tends to be influenced and explained by its past values. The structural lags are established by using minimum Akaike's information criteria (AIC), Pesaran et al. [35] suggested using the standard joint significance *F* test on the lagged levels variables. After regression of Eq. (5), the Wald test (*F*-statistic) was computed to differentiate the long-run relationship between the concerned variables. The Wald test can be carry out by imposing restrictions on the estimated long-run coefficients of EPC, ATM, TOPO, LOT, WS and GROWTH. The null and alternative hypotheses are as follows:

$H_0: \beta_1=\beta_2=\beta_3=\beta_4=\beta_5=\beta_6=0$ (no long-run relationship)

Against the alternative hypothesis

$H_A: \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6 \neq 0$ (a long-run relationship exists)

The computed *F*-statistic value will be evaluated with the critical values tabulated in Table CI (iii) of Pesaran et al. [35]. According to these authors, the lower bound critical values assumed that the explanatory variables x_t are integrated of order zero, or I(0), while the upper bound critical values assumed that x_t are integrated of order one, or I(1). Therefore, if the computed *F*-statistic is smaller than the lower bound value, then the null hypothesis is not rejected and we conclude that there is no long-run relationship between energy consumption and its determinants. Conversely, if the computed *F*-statistic is greater than the upper bound value, then variables among have a long-run level relationship. On the other hand, if the computed *F*-statistic falls between the lower and upper bound values, then the results are inconclusive.

The Granger causality test is then used to determine the direction of causality among the six broad categories of the variables in this study. However, if the variables are I(1) and

cointegrated, the Granger causality test within the first difference VAR model will be misleading [36]. In such circumstances, Granger causality should be tested using the ECM as follows:

$$\begin{aligned}\Delta \ln (\mathrm{EPC})_t = \alpha_1 &+ \sum_{i=1}^{k} k1i\Delta \ln (\mathrm{EPC})_{t-i} + \sum_{i=0}^{k} \nu 1i\Delta \ln (\mathrm{ATM})_{t-i} \\ &+ \sum_{i=0}^{k} \delta 1i\Delta \ln (\mathrm{TOPO})_{t-i} + \sum_{i=0}^{k} \theta 1i\Delta \ln (\mathrm{LOT})_{t-i} \\ &+ \sum_{i=0}^{k} \gamma 1i\Delta \ln (\mathrm{WS})_{t-i} \\ &+ \sum_{i=0}^{k} \theta 1i\Delta \ln(\mathrm{GROWTH}) + \vartheta 1\varepsilon_{t-1} + \xi 1t \end{aligned} \tag{6}$$

$$\begin{aligned}\Delta \ln (\mathrm{ATM})_t = \alpha_1 &+ \sum_{i=1}^{k} k1i\Delta \ln (\mathrm{ATM})_{t-i} + \sum_{i=0}^{k} \nu 1i\Delta \ln (\mathrm{EPC})_{t-i} \\ &+ \sum_{i=0}^{k} \delta 1i\Delta \ln (\mathrm{TOPO})_{t-i} + \sum_{i=0}^{k} \theta 1i\Delta \ln (\mathrm{LOT})_{t-i} \\ &+ \sum_{i=0}^{k} \gamma 1i\Delta \ln (\mathrm{WS})_{t-i} + \sum_{i=0}^{k} \theta 1i\Delta \ln(\mathrm{GROWTH}) \\ &+ \vartheta 1\varepsilon_{t-1} + \xi 1t \end{aligned} \tag{7}$$

$$\begin{aligned}\Delta \ln (\mathrm{TOPO})_t = \alpha_1 &+ \sum_{i=1}^{k} k1i\Delta \ln (\mathrm{TOPO})_{t-i} + \sum_{i=0}^{k} \nu 1i\Delta \ln (\mathrm{ATM})_{t-i} \\ &+ \sum_{i=0}^{k} \delta 1i\Delta \ln (\mathrm{EPC})_{t-i} + \sum_{i=0}^{k} \theta 1i\Delta \ln (\mathrm{LOT})_{t-i} \\ &+ \sum_{i=0}^{k} \gamma 1i\Delta \ln (\mathrm{WS})_{t-i} + \sum_{i=0}^{k} \theta 1i\Delta \ln(\mathrm{GROWTH}) \\ &+ \vartheta 1\varepsilon_{t-1} + \xi 1t \end{aligned} \tag{8}$$

$$\begin{aligned}\Delta \ln (\mathrm{LOT})_t = \alpha_1 &+ \sum_{i=1}^{k} k1i\Delta \ln (\mathrm{LOT})_{t-i} + \sum_{i=0}^{k} \nu 1i\Delta \ln (\mathrm{ATM})_{t-i} \\ &+ \sum_{i=0}^{k} \delta 1i\Delta \ln (\mathrm{TOPO})_{t-i} + \sum_{i=0}^{k} \theta 1i\Delta \ln (\mathrm{EPC})_{t-i} \\ &+ \sum_{i=0}^{k} \gamma 1i\Delta \ln (\mathrm{WS})_{t-i} + \sum_{i=0}^{k} \theta 1i\Delta \ln(\mathrm{GROWTH}) \\ &+ \vartheta 1\varepsilon_{t-1} + \xi 1t \end{aligned} \tag{9}$$

$$\begin{aligned}\Delta \ln (\mathrm{WS})_t = \alpha_1 &+ \sum_{i=1}^{k} k1i\Delta \ln (\mathrm{WS})_{t-i} + \sum_{i=0}^{k} \nu 1i\Delta \ln (\mathrm{ATM})_{t-i} \\ &+ \sum_{i=0}^{k} \delta 1i\Delta \ln (\mathrm{TOPO})_{t-i} + \sum_{i=0}^{k} \theta 1i\Delta \ln (\mathrm{LOT})_{t-i} \\ &+ \sum_{i=0}^{k} \gamma 1i\Delta \ln (\mathrm{EPC})_{t-i} + \sum_{i=0}^{k} \theta 1i\Delta \ln(\mathrm{GROWTH}) \\ &+ \vartheta 1\varepsilon_{t-1} + \xi 1t \end{aligned} \tag{10}$$

$$\begin{aligned}\Delta \ln (\mathrm{GROWTH})_t = \alpha_1 &+ \sum_{i=1}^{k} k1i\Delta \ln (\mathrm{GROWTH})_{t-i} \\ &+ \sum_{i=0}^{k} \nu 1i\Delta \ln (\mathrm{ATM})_{t-i} + \sum_{i=0}^{k} \delta 1i\Delta \ln (\mathrm{TOPO})_{t-i} \\ &+ \sum_{i=0}^{k} \theta 1i\Delta \ln (\mathrm{LOT})_{t-i} + \sum_{i=0}^{k} \gamma 1i\Delta \ln (\mathrm{WS})_{t-i} \\ &+ \sum_{i=0}^{k} \theta 1i\Delta \ln(\mathrm{EPC}) \\ &+ \vartheta 1\varepsilon_{t-1} + \xi 1t \end{aligned} \tag{11}$$

The equations above consist of short and long-run elements. Δ and ln are the notations for first difference and natural logarithm, respectively. The residuals $\zeta 1t$ are assumed to be normally distributed and white noise. From the above equations, ε_{t-1} is the one period lagged error-correction term derived from the cointegrating equation. However, in the absence of cointegration, the ε_{t-1} term will be excluded from the above equation, thus it remains as the standard first difference VAR model. To examine the short run Granger causality, we apply the standard Wald test on the first difference lagged explanatory variables. However, to examine the long-run Granger causality, we employ the standard Wald test on both the first difference lagged explanatory variables and the ε_{t-1} term.

Table 3
The unit root test results.

Variables	ADF (South Asia)	ADF (MENA)	ADF (Sub-Saharan Africa)	ADF (East Asia and Pacific)	ADF (World)
EPC	I(1)	I(1)	I(1)	I(1)	I(1)
AP	I(0)	I(1)	I(1)	I(0)	I(1)
CO_2	I(1)	I(1)	I(1)	I(0)	I(0)
INE	I(1)	I(0)	I(0)	I(1)	I(1)
ME	I(1)	I(0)	I(0)	I(1)	I(1)
DFET	I(1)	I(1)	I(1)	I(0)	I(0)
FD	I(0)	I(1)	I(1)	I(0)	I(0)
MRD	I(0)	I(1)	I(1)	I(0)	I(1)
URB	I(0)	I(1)	I(1)	I(0)	I(1)
AL	I(0)	I(1)	I(1)	I(0)	I(1)
BS[a]	I(0)	I(1)	I(1)	I(0)	I(0)
MS[a]	I(1)	I(1)	I(1)	I(1)	I(1)
PS[a]	I(1)	I(1)	I(1)	I(0)	I(1)
FS[a]	I(1)	I(1)	I(1)	I(0)	I(1)
AIL	I(1)	I(1)	I(1)	I(0)	I(1)
GWR	I(1)	I(1)	I(1)	I(0)	I(1)
CW	I(0)	I(1)	I(0)	I(0)	I(1)
GDPPC	I(0)	I(0)	I(0)	I(0)	I(0)
IAV	I(1)	I(1)	I(1)	I(1)	I(0)
GDPENRG	I(1)	I(0)	I(1)	I(1)	I(0)
PG	I(1)	I(0)	I(1)	I(1)	I(0)

Note: The null hypothesis is that the series is non-stationary, or contains a unit root. The rejection of the null hypothesis is based on MacKinnon critical values. The lag length are selected based on SIC criteria, this ranges from lag zero to lag four. The model with constant and trend was used to estimate the unit root tests. I(1) shows the variables are non-stationary at level but stationary becomes after first difference. I(0) shows the variables are stationary at their level.

[a] Where data covers the period 199–2011.

3. Results

The standard Augmented Dickey–Fuller (ADF) and Phillips Perron (PP) unit root test was exercised to check the order of integration of these variables. The results obtained are reported in Table 3. Based on the ADF unit root test statistic, it was concluded that most of the variables are non-stationary at their level but stationary after taking first difference i.e., I(1) variables, however, remaining of the variables are stationary at their level i.e., I(0) variables.

The relationship between dependent variable (i.e., energy consumption) and the independent variables (i.e., atmosphere, topography, living organisms threatened, water system and economic growth) is observed using the multivariate cointegration methodology proposed by Johansen [37] and Johansen and Juselius [33]. Johansen's Cointegration Test designates at least one cointegrating vector. Thus, long-run relationship is maintained by the data generating method. Using Johansen and Juselius [33] multivariate cointegration tests, the study finds that a statistically significant relationship exists between climate change variables on energy consumption in different regions of the world. The following cointegrating vector has been determined in Table 4.

As evident in Table 4, there are three cointegration equations in South Asia, four in MENA region, seven cointegration equations in Sub-Saharan Africa, six in East Asia and Pacific region and five cointegration equations in the overall data of the world, involving

Table 4
Cointegration test results.

4A: Multivariate Johansen–Juselius cointegration test					
Regions	South Asia	MENA	Sub-Saharan Africa	East Asia and Pacific	World
Number of cointegrating equations	Three cointegration equations	Four cointegration equations	Seven cointegration equations	Six cointegration equations	Five cointegration equations
Regions	Model				Wald F-statistics
4B: Bounds testing approach to cointegration					
South Asia	F_{EPC}(EPCIATM, TOPO, LOT, WS, GROWTH)				11.28*
MENA	F_{EPC}(EPCIATM, TOPO, LOT, WS, GROWTH)				6.96*
Sub-Saharan Africa	F_{EPC}(EPCIATM, TOPO, LOT, WS, GROWTH)				13.28*
East Asia and Pacific	F_{EPC}(EPCIATM, TOPO, LOT, WS, GROWTH)				212.85*
World	F_{EPC}(EPCIATM, TOPO, LOT, WS, GROWTH)				172.95*
Significance level (%)	Lower bounds, I(0)			Upper bounds, I(1)	
Narayan [39] critical value bounds of the F-statistic: intercept and no trend					
1	4.590			6.368	
5	3.276			4.630	
10	2.696			3.895	
	South Asia	MENA	Sub-Saharan Africa	East Asia and Pacific	World
Diagnostic tests					
Adjusted R^2	0.452	0.725	0.614	0.385	0.458
F-statistics	112.45*	78.352*	16.852*	3.258**	4.752*
JB (χ^2_{NORMAL})	$p>0.050$	$p>0.050$	$p>0.050$	$p<0.050$	$p>0.050$
LM (χ^2_{SERIAL})	$p>0.050$	$p<0.050$	$p>0.050$	$p>0.050$	$p>0.050$
ARCH (χ^2_{ARCH})	$p>0.050$	$p<0.050$	$p>0.050$	$p>0.050$	$p>0.050$
Ramsey RESET (χ^2_{RESET})	$p>0.050$	$p>0.050$	$p>0.050$	$p<0.050$	$p<0.050$
CUSUM	Stable at 5% level	Stable at 5% level	Stable at 5% level	Stable at 5% level	Stable at 5% level
CUSUM of squares	Stable at 5% level	Stable at 5% level	Stable at 5% level	Stable at 5% level	Stable at 5% level

* Denote significance at the 1% levels.
** Denote significance at the 5% levels.

variables i.e., EPC, ATM, TOPO, LOT, WS and GROWTH respectively. The presence of the cointegration vectors shows that there exists a long-run relationship among the variables. This study further examined the existence of long-run relationship between the variables. We used a Hendry's general-to-specific modeling approach and selected the maximum lag order of three for the conditional ARDL-VECM. Maximum lag order of three years is sufficient to capture the system's dynamics' for the yearly data analysis [38]. Table 4B reports the results of bounds test with *F*-statistics when each variable is considered as a dependent variable in ARDL-OLS regressions. Based on the Narayan [39] critical values, all model specification i.e., F_{EPC} is significant at 1% level. Thus the null hypothesis of no cointegration is rejected in all regions of the world, implying long-run cointegration relationships between the variables.

A number of diagnostic tests are conducted to ensure that the selected autoregressive distributed lag (ARDL) model is appropriate. Overall, in majority of the region, the selected ARDL model is free from heteroskedasticity, serial correlation and general specification error, except, normality issue has found in East Asia and Pacific region, autocorrelation problem exists in MENA region, heteroskedastisity problem in MENA region and specification error of the model in East Asia and Pacific and World. Moreover, both CUSUM and CUSUM of square tests reject the presence of structural break. Table 4, panel B, presents the calculated *F*-statistic for cointegration, the critical values provided by Narayan [39] and the diagnostic tests. We find that the calculated *F*-statistic is greater than the 1% upper bounds critical values. Hence, we reject the null hypothesis of no cointegration relationship among the variables. This is corroborated by the results of the Johansen–Juselius cointegration test. Since the suggestions of both cointegration tests are consistent, we confirm that the variables are cointegrated and that the cointegration results are robust.

In order to check the stability of the long-run and short-run relationship among energy and climate change variables, we assess the Error Correction Model in Table 5.

The long-run results are presented in Table 5A. In general, majority of cases indicate that climatic variables positively affect electric power consumption in different regions of the world. However, the intensity of the coefficient varies region to region. In some regions, climatic variables are more elastic in nature while in other regions, there is less elastic in nature which implies that little change in electric power consumption leads to greater change in climatic variables or vice versa. The overall results conclude that climate change leads to species range shifts and consequently to changes in diversity [40]. Climate change affects ocean conditions, including temperature, salinity, ice coverage, currents, oxygen level, acidity and consequently growth, body size, distribution, productivity and abundance of marine species, including those that are exploited by fisheries. Over a range of greenhouse gas emission scenarios, changes in the marine environment are predicted to be more rapid in the 21st century with implications for marine ecosystems and dependent industries [41]. The increased energy efficiency, implementation of energy savings projects, energy conservation, and energy infrastructure outsourcing reduce the level of pollution produced by urban areas [11].

As the variables are cointegrated, the short run elasticities are evaluated using the ECM. Table 5B shows the result of short-run elasticities and diagnostic tests. The coefficient for error correction term is negative and statistically significant at the 1% and 5% level, except MENA region, where ECM term is insignificant. The result shows the presence of a long-run relationship among energy and climate variables. The result shows that range between 10.2% minimum to 56.8% maximum variation of energy consumption in South Asia, Sub-Saharan Africa, East Asia and Pacific and the World are due to disequilibrium. Moreover, if the system exposes to shock, energy

Table 5
Long-run and short-run elasticities dependent variable: Δ ln(EPC).

Variables	Coefficients (South Asia)	Coefficients (MENA)	Coefficients (Sub-Saharan Africa)	Coefficients (East Asia and Pacific)	Coefficients (World)
5A: Long-run results					
AP	Positive, < 1*	Positive, < 1*	Positive, < 1**	Positive, < 1	Positive, < 1
CO_2	Positive, < 1*	Positive, > 1	Positive, < 1*	Positive, > 1**	Positive, < 1*
INE	Negative, < 1	Positive, < 1*	Positive, < 1*	Positive, < 1*	Positive, > 1*
ME	Positive, < 1*	Positive, < 1*	Positive, < 1*	Positive, < 1*	Positive, < 1*
DFET	Positive, < 1*	Negative, < 1	Positive, > 1***	Positive, < 1*	Positive, < 1*
FD	Negative, < 1	Positive, < 1*	Positive, < 1*	Negative, < 1	Positive, < 1*
MRD	Positive, < 1*	Positive, < 1*	Positive, < 1*	Positive, > 1**	Positive, < 1*
URB	Positive, < 1*	Positive, < 1*	Positive, < 1*	Positive, < 1*	Negative, < 1
AL	Positive, < 1*	Positive, < 1*	Positive, < 1*	Positive, < 1*	Negative, < 1
BS[a]	Negative, < 1	Negative, < 1	Positive, < 1*	Negative, < 1	Positive, < 1*
MS[a]	Negative, < 1	Negative, < 1	Positive, < 1	Positive, < 1*	Positive, < 1*
PS[a]	Positive, < 1	Positive, < 1	Positive, < 1	Positive, < 1*	Positive, < 1*
FS[a]	Positive, < 1	Positive, < 1	Negative, < 1	Positive, < 1*	Positive, < 1
AIL	Positive, < 1*	Positive, < 1***	Negative, < 1	Positive, < 1*	Positive, < 1
GWR	Positive, < 1*	Positive, < 1	Positive, < 1*	Positive, < 1*	Positive, < 1
CW	Positive, > 1*	Negative, < 1	Negative, < 1	Positive, < 1*	Positive, < 1*
GDPPC	Positive, < 1*	Negative, < 1	Positive, < 1*	Positive, < 1*	Positive, < 1*
IAV	Positive, < 1*	Positive, < 1*	Positive, > 1*	Positive, < 1*	Positive, < 1
GDPENRG	Positive, < 1*	Negative, < 1	Positive, < 1*	Positive, < 1*	Positive, < 1*
PG	Positive, > 1*	Negative, < 1	Positive, < 1*	Positive, < 1	Positive, < 1
5B: Short-run results					
AP	Positive, < 1	Positive, < 1*	Positive, < 1*	Positive, < 1	Positive, < 1*
CO_2	Positive, < 1*	Positive, < 1	Positive, < 1*	Negative, > 1*	Positive, < 1
INE	Positive, < 1*	Negative, < 1	Positive, < 1*	Positive, < 1*	Positive, < 1*
ME	Positive, > 1*	Positive, < 1	Positive, < 1*	Positive, < 1*	Positive, < 1*
DFET	Positive, < 1*	Positive, < 1*	Positive, < 1	Negative, < 1*	Positive, < 1
FD	Positive, < 1*	Negative, < 1*	Positive, < 1*	Positive, > 1*	Positive, < 1*
MRD	Positive, < 1*	Negative, < 1*	Positive, < 1*	Positive, < 1	Positive, < 1*
URB	Positive, < 1*	Positive, < 1	Negative, < 1*	Positive, < 1	Positive, < 1*
AL	Positive, < 1*	Positive, < 1	Positive, > 1*	Positive, < 1*	Negative, < 1*
BS[a]	Negative, < 1	Positive, < 1*	Positive, < 1	Positive, < 1	Positive, < 1*
MS[a]	Negative, < 1	Positive, < 1*	Positive, < 1	Positive, < 1	Positive, < 1*
PS[a]	Positive, < 1	Positive, < 1*	Negative, < 1	Positive, < 1	Positive, < 1
FS[a]	Positive, < 1	Negative, < 1	Positive, < 1	Positive, < 1	Positive, < 1*
AIL	Positive, < 1*	Positive, < 1*	Positive, < 1	Positive, < 1*	Positive, < 1
GWR	Positive, > 1*	Positive, < 1	Negative, < 1*	Positive, < 1*	Negative, < 1*
CW	Positive, < 1*	Negative, < 1	Positive, < 1*	Positive, < 1	Positive, < 1*
GDPPC	Negative, < 1*	Positive, < 1	Positive, < 1*	Positive, < 1	Positive, < 1*
IAV	Positive, < 1*	Positive, < 1	Negative, > 1*	Positive, < 1*	Positive, < 1*
GDPENRG	Positive, < 1*	Positive, < 1*	Positive, < 1*	Positive, > 1*	Positive, > 1*
PG	Positive, > 1*	Negative, < 1	Positive, > 1*	Positive, < 1	Positive, < 1*
ε_{t-1}	-0.485**	0.314	-0.102**	-0.568*	-0.274*
Diagnostic Tests					
Adjusted R^2	0.401	0.565	0.587	0.412	0.389
F-statistics	68.25*	118.58*	6.958*	2.258**	5.258*
JB (χ^2_{NORMAL})	$p > 0.050$	$p > 0.050$	$p > 0.050$	$p < 0.050$	$p > 0.050$
LM (χ^2_{SERIAL})	$p > 0.050$	$p < 0.050$	$p < 0.050$	$p > 0.050$	$p < 0.050$
ARCH (χ^2_{ARCH})	$p > 0.050$	$p < 0.050$	$p > 0.050$	$p > 0.050$	$p > 0.050$
Ramsey RESET (χ^2_{RESET})	$p > 0.050$	$p < 0.050$	$p > 0.050$	$p < 0.050$	$p < 0.050$
CUSUM	Stable at 5% level	Stable at 5% level	Stable at 5% level	Stable at 5% level	Stable at 5% level
CUSUM of squares	Stable at 5% level	Stable at 5% level	Stable at 5% level	Stable at 5% level	Stable at 5% level

Probability values are quoted in square brackets. LM (I) tests for the null of 1st order serial correlation amongst the residuals; Het: a test based on regression of squared residuals on a constant and squares of the fitted values; ARCH: a test for first-order autoregressive conditional Heteroscedasticity effects; RESET: Ramsey's Regression Specification Error/'-test with (m, n) degrees of freedom; and the Jarque–Bera X2(2) LM test for normality of residuals.
"a" indicates that the continous time serial data is not available for the said variables, therefore, forward and backward interpolation technique is used to fill the missing values of the data.

* Denote statistical significance at the 1% levels.
** Denote statistical significance at the 5% level.
*** Denote statistical significance at the 10% levels.

consumption takes nearly a year to converge to its long-run equilibrium. Regarding all other explanatory variables, we find that in the short run, climatic variables by and large are statistical significant at the 1%, 5% and 10% level. The value of R^2 adjusted indicates the ranges between 38.9% and 58.7% variation in dependent variable has been explained by variations in independent variables. *F*-value is higher than its critical value suggesting a good overall significance of the estimated model. Therefore, fitness of the model is acceptable empirically. The model seems to be robust to various departures from standard regression assumptions in terms of residual correlation, like Heteroscedasticity, Autoregressive Conditional Heteroscedasticity (ARCH), misspecification of functional form, or non-normality of residuals. This result tends to suggest that, in majority of the world regions, the impact of any structural change over the entire sample period does not appear to be significant at least in terms of model stability.

Table 6
Long-run Granger causality test – VECM (Causality between energy consumption and climate change variables).

Variables	Causality (South Asia)	Causality (MENA)	Causality (Sub-Saharan Africa)	Causality (East Asia and Pacific)	Causality (World)
Energy consumption to atmosphere					
EPC to AP	✓	–	✓	✓	–
EPC to CO_2	✓	✓	✓	✓	✓
EPC to INE	✓	✓	✓	–	–
EPC to ME	✓	–	✓	✓	✓
EPC to DFET	✓	✓	–	✓	✓
Energy consumption to topography					
EPC to FD	✓	✓	✓	–	✓
EPC to MRD	✓	–	–	–	–
EPC to AL	–	✓	✓	✓	–
EPC to URB	✓	–	✓	–	✓
Energy consumption to living organisms threatened					
EPC to BS	–	–	–	–	–
EPC to MS	–	–	–	–	–
EPC to PS	–	✓	–	–	✓
EPC to FS	✓	–	–	✓	–
Energy consumption to water system					
EPC to GWR	✓	✓	–	–	✓
EPC to AIL	✓	–	✓	✓	✓
EPC to CW	✓	✓	–	–	–
Energy consumption to economic growth					
EPC to GDPPC	✓	✓	–	✓	✓
EPC to IVA	–	✓	–	✓	✓
EPC to GDPENRG	✓	✓	✓	–	–
EPC to PG	✓	–	✓	–	✓
Atmosphere to energy consumption					
AP to EPC	–	–	–	–	–
CO_2 to EPC	–	–	–	–	–
INE to EPC	✓	✓	✓	✓	✓
ME to EPC	–	–	–	–	–
DFET to EPC	✓	–	–	✓	✓
Topography to energy consumption					
FD to EPC	–	–	–	–	–
MRD to EPC	–	–	–	–	–
AL to EPC	–	–	–	–	–
URB to EPC	✓	✓	✓	✓	✓
Living organisms threatened to energy consumption					
BS to EPC	–	–	–	–	–
MS to EPC	–	–	–	–	–
PS to EPC	–	–	–	–	–
FS to EPC	–	–	–	–	–
Water system to energy consumption					
GWR to EPC	–	–	–	–	–
AIL to EPC	–	–	–	–	–
CE to EPC	–	–	–	–	–
Economic growth to energy consumption					
GDPPC to EPC	✓	✓	–	✓	✓
IVA to EPC	✓	✓	✓	–	✓
GDPENRG to EPC	✓	✓	–	✓	–
PG to EPC	✓	✓	✓	✓	✓

Note: ✓ indicates causality exists between the variables while dash (–) represents no causality between the variables.

As the variables are cointegrated, we proceed to examine the short and the long-run Granger causality in the ECM framework. Table 6 presents the results of Granger causality among energy consumption and climate change variables. The overall results conclude that at large, there is unidirectional causality running towards electric power consumption to climate change variables which implies that electric power consumption changes the global weather, sound and effective energy consumption strategy may reduce the burden of global warming situation in the world.

The long-run causalities have some important policy implications in the context of different regions of the world. First, the finding of unidirectional Granger causality between energy consumption and climate change variables suggests that per capita electric power consumption is the stimulating input for enhancing climatic variables and economic growth [42]. The findings further indicate the neutrality hypothesis which treats that energy consumption as an insignicant part of climate change variables and economic output which shows no causality between these variables [43].

The awareness of global environmental challenges makes it essential that there is some understanding of the causal effects of energy consumption on climate change and development. The result shows that there is a bidirectional causality running between industrial nitrous oxide emissions to electric power consumption in South Asia, MENA and Sub-Saharan African region. Similarly, there is a bidirectional causality running between droughts, floods and extreme temperature to electric power consumption in South Asia, East Asia and Pacific and the World. Among topographic variables, only urbanization is the only variable which cause electric power consumption and vice versa in South Asia, Sub-Saharan Africa and World. Most of the growth variables have shown bidirectional causality with the electric power consumption in different regions of the world which implies that any policy to reduce energy consumption (and hence emissions) would have an effect on climate change variables and overall region's development.

4. Conclusion

This study presents new theoretical and empirical insights into the analysis of the causal relationship between energy consumption and climate change variables when considering a sample of five broader regions of the world. The results support four alternative and equal plausible hypotheses among different variables in the different regions of the world. First, the "conservation hypothesis" that shows a unidirectional causality running from climatic variables to energy consumption. The energy conservation policies resulting in a reduction of energy consumption have little or no negative effects on climatic variables i.e., industrial nitrous oxide emission in East Asia and Pacific region and World, urbanization in MENA and East Asia and Pacific region, industry value added in South Asia and Sub-Saharan Africa, GDP per energy use in East Asia and Pacific region, and finally, population growth in East Asia and Pacific region. Secondly, the "growth hypothesis" which shows climatic change is dependent on energy use, which means there is a unidirectional causality running from energy to climatic factors. A significant change in climatic factors, knowing that energy use is not positive, it is due to improper use or to energy inefficiency i.e. which leads to distortions in climatic factors. Thirdly, the "feedback hypothesis" that suggests the existence of bidirectional causality between energy consumption and climatic factors in different regions of the world. In this case an energy policy oriented towards improving the energy efficiency would little or no harm climatic factors. Finally, the "neutrality hypothesis" that shows there is no causal relationship. Similar to the assumption of conservation hypothesis, an energy conservation policy has no or little effect on climatic factors.

The following conclusion has been emerged from the analysis i.e.

- The climate change poses challenges to energy suppliers and users in terms of potential increase in the economic cost of energy use [44].

- Rise in the average and extreme temperatures increases electricity demand for cooling down temperatures in different regions of the world [45].
- Climate change has larger impact on the peak electricity demand than on the average monthly electricity demand [46].
- Climate change risks oil and gas supply activities in vulnerable coastal areas, offshore production areas, and tundra areas [47].
- Both climate change and rising concentrations of atmospheric carbon dioxide affect bioenergy production potentials [48].
- Expected seasonal and chronic water scarcity present risk of disruptions in the supply of electricity in many different regions of the world [49].
- Climate change affects the geographical pattern of renewable energy supply in the different regions of the world [50].
- Expected reductions in precipitation in the form of snowfall reduce hydropower production [51].
- In most of the cases analyzed, adaptation measures can reduce risks and prospects of negative consequences of energy supply and use [52].
- Energy system resilience against climate change can be achieved by investing in the research and development programs [53].
- Most of the vulnerabilities and risks from energy supply and demand reflect relatively fine-grained place-based differences in situations [54].
- The variability of risks from weather-related events in both time and space increases with climate change [55].
- Impact of Climate change interacts with regulatory environment [56].
- Despite uncertainties about the impact of climate change in the future, robust risk management strategies can be developed in an iterative manner that incorporates continuous observation, evaluation, and learning [57].
- A critical step in developing RRMS (robust risk management strategy) is to conduct vulnerability assessment of energy users and suppliers in advance [58].
- Improvement in the existing knowledge about vulnerabilities and risk management strategies is essential for effective climate change risk management in the energy sector [59].
- A self-sustaining long term assessment plan with commitment is needed to improve the scientific base for streamlining long term solutions of climate change [60].
- Self-sustaining assessment plans provide value to all stakeholders of climate change in the regions [61].

These conclusion lead us to join our heads to have the efficient and sustainable energy consumption which have less or almost negligible impact on our nature format.

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